APPENDIX D
POPULATION CHANGE CRITERIA

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Population Change Criteria Overview

The population change criteria (PCC) provide a novel performance test for evaluating whether a threatened population has recovered and is no longer in danger of extinction. The approach starts with the development of a viability curve, which describes the relationships among population abundance, productivity, and extinction risk (Figure D.1). The extinction risk experienced by a population is a function of both the population's productivity and size (Musick 1999, McElhany et al. 2000). We define productivity as the number of returns produced per spawner, when the population is at low density relative to carrying capacity. All else being equal, a population with a high average productivity could persist at a lower abundance than a population with a low average productivity. This is because a population with high average productivity would have a higher probability of returning to the original abundance if perturbed to low abundance than a population with low average productivity. A high-productivity population could be characterized as being more resilient than a low-productivity population. The amount of environmental variation affects the likelihood that a population will be perturbed to low abundance and is another key parameter in the estimation of extinction risk. With regard to population size, all else being equal, the smaller a population is, the more likely it is to fluctuate to extinction (Thomas 1990, Lande 1993). The viability curve can be estimated using a population projection model that incorporates abundance, productivity, environmental

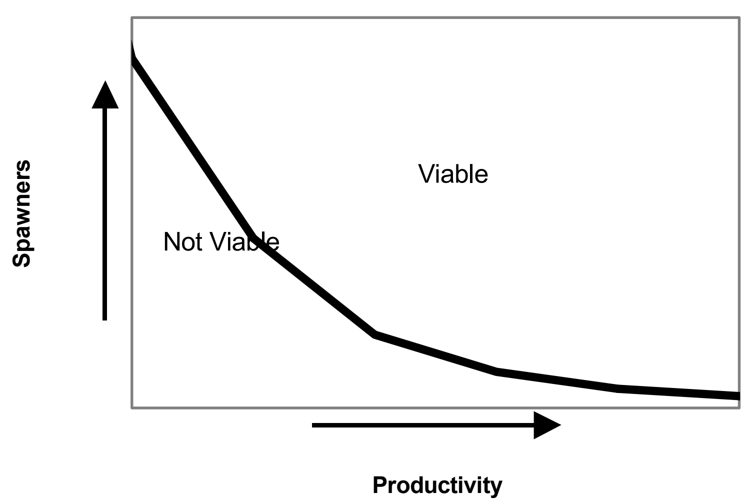


Figure D.1 The relationship between productivity, population size, and extinction risk. The curve represents combinations of size and productivity that have exactly the acceptable extinction risk.

variability, and any other factor considered relevant for estimating extinction risk.

Key issues with developing criteria from viability curves are determining an appropriate form for the population projection model and determining how to estimate parameters. As described in the first section of this appendix, the projection model used for the PCC viability curve is relatively simple and is well described in the population dynamics literature. The next section of this appendix ("Projection Model and Minimum-Size Estimation Methods") describes the distinguishing features of the PCC approach. These features involve the method used to estimate productivity and the development of a population performance test.

Projection Model and Minimum-Size Estimation Methods

Model Overview

We calculated a viability curve using a population projection model of stochastic exponential growth with a ceiling and a lower critical threshold (Figures D.2 through D.5).

$$\begin{aligned}
&N_{t+1} = 0 \text{ if } N_t \le QET \\
&N_{t+1} = N_t e^r \text{ if } \mathrm{QET} < N_t \le k \\
&N_{t+1} = ke^r \quad \text{if } N_t > k \\
&\text{where } r \approx Normal(\mu, \sigma).
\end{aligned} \qquad \text{Eq. 1}$$

where

N_t is the population size at time t,
k is the maximum size of the reproductive population (i.e., "ceiling"),
r is a stochastic parameter describing the per capita reproductive rate, and
QET is the quasi-extinction threshold.

The parameter μ is the median per capita growth rate of a population below k, and σ^2 describes the environmental variability in growth rate ("process variance"). The normal distribution of r is a theoretical consequence of the central limit theorem applied to a multiplicative survival process (Hilborn and Walters 1992). In the nomenclature of recruitment models, this is a "stochastic hockey-stick" model, as compared to a Ricker or Beverton-Holt model (Barrowman and Myers 2000). The median annual growth rate, λ, for a population below k is $\lambda = e^{\mu}$. We will refer to the median growth rate of a population below k as the productivity of the population, and represent productivity with the symbol γ. The Ricker and Beverton-Holt recruitment models have a productivity parameter often symbolized as α, which represents the "intrinsic productivity" or number of returns per spawner if there was only one spawner (Hilborn and Walters 1992). Since the interpretation and values of the parameters in the hockey-stick and the other models differ, we have adopted a different symbol to avoid confusion. If $\gamma > 1$, the equilibrium mean abundance with this model is near k. If $\gamma < 1$, the equilibrium mean abundance is 0 (extinction). Extinction risk using the model is estimated as the probability that a population starting at some initial population size, N_0, declines to the QET within a given time horizon. The extinction risk is estimated by simulating the population process with some given growth rate and process variance to produce many population trajectories, then calculating the fraction of simulated population trajectories that declined to QET within the specified time period.

Because of the age structure of salmon populations, the population dynamics model was applied to a four-year running sum of annual spawner counts as described in Holmes (2001) and McClure et al. (in review). Thus,

$$N_t = \sum_{i=0}^{3} S_{t-i} \ ,$$

where N_t is as above and S_t is the number of spawners in year t. Both initial population sizes and QET are stipulated in the model in terms of four-year sums, which is equivalent to an average annual spawner count over four years of $N/4$.

Using this model, we identify the minimum population size for a given productivity as the initial population size, N_0, which just produces an acceptable extinction risk (Figure D.2). The minimum size is found using a simple search algorithm that tests the extinction risk associated with a number of different potential initial population sizes. If a population were to start out at a size smaller than the minimum size, the extinction risk would be too high; and if the initial population size were larger, the extinction risk would be lower than the acceptable risk originally specified. The variance parameter of the model, σ^2, is an empirical estimate based on recent historical abundance time-series data for the population or species (see below for estimation approach). The population ceiling, k, is set as the initial population size. Thus, we estimate the minimum population size under the scenario that the minimum population size is also the population ceiling. This effectively allows the minimum population size estimate to also be an estimate of minimum carrying capacity. We can seldom estimate with confidence the carrying capacity of a population, and this approach provides a precautionary estimate of the minimum population size, since a population constrained by a low ceiling has a higher extinction risk than a population without a ceiling.

This is a very simplified model of salmonid dynamics, which does not include many of the features associated with salmon biology, such as ocean regime shifts, short-term temporal autocorrelations, complex recruitment functions, etc. We addressed these issues in a variety of ways, and the final criteria reflect consideration of more factors than are reflected in Equation 1 alone.

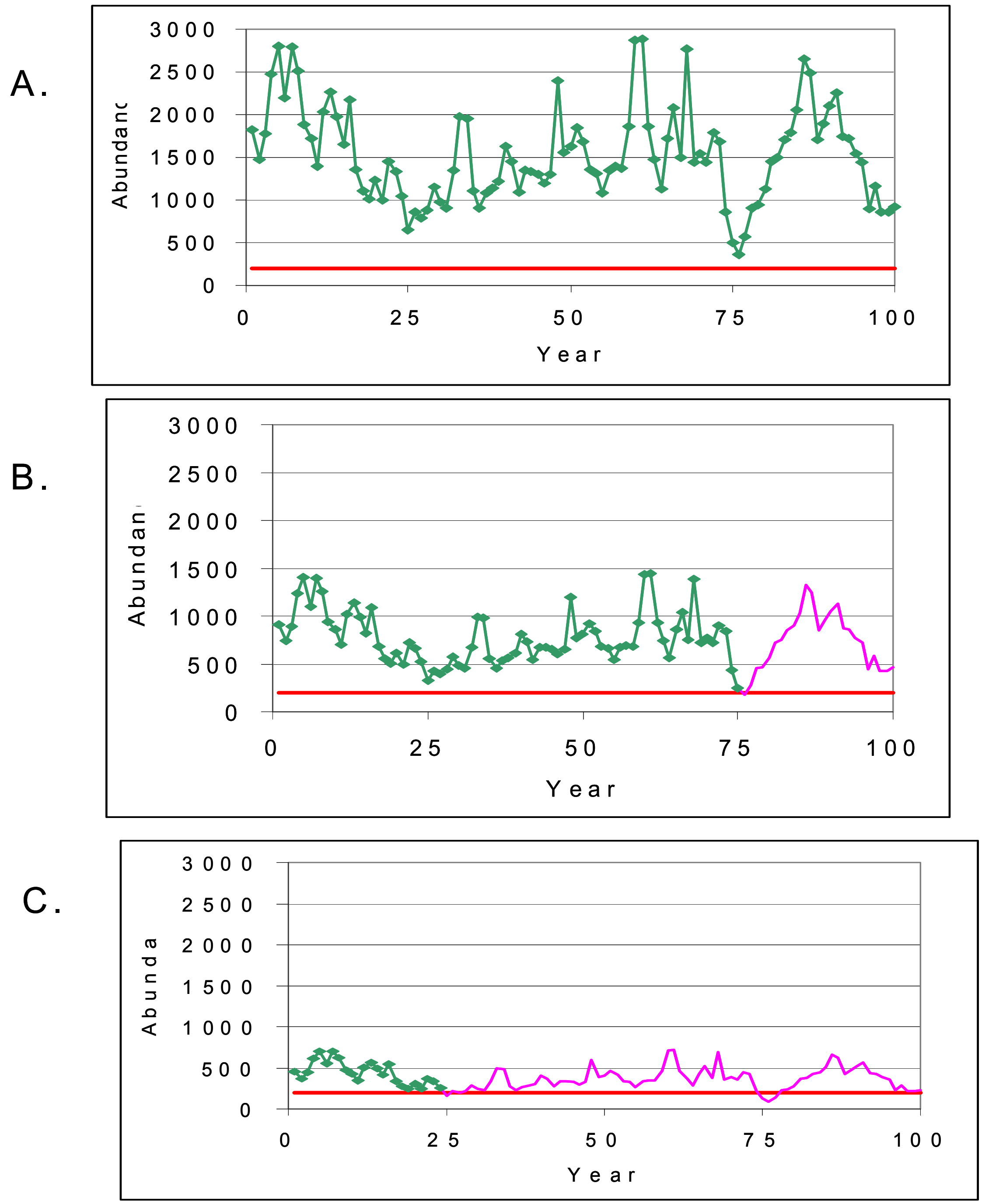


Figure D.2 Simulated population trajectories illustrating the relationship between population abundance, environmental variability, and extinction risk. The lower line indicates the quasi-extinction threshold (QET); populations that drop below this level are considered functionally extinct.

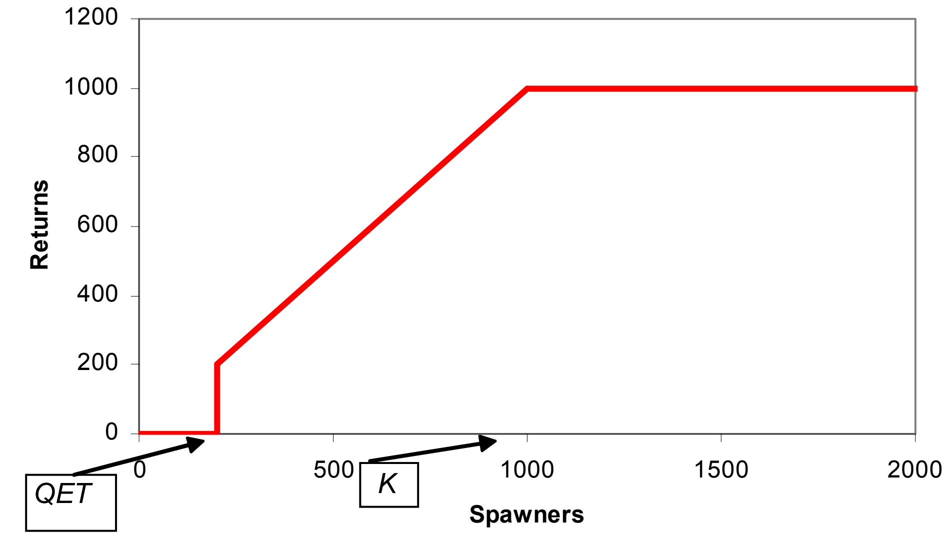


Figure D.3 Conceptual drawing of recruitment function for projection model to identify minimum population size. This is a hockey-stick model, with a depensitory threshold. Below *QET* spawners, the population is considered extinct. Above *k* spawners, the returns are constant. The slope of the line at abundances between *QET* and *k* is an indication of the productivity of the population (γ). This graph represents only the deterministic skeleton of the model. Productivity is actually a stochastic variable driven by environmental variation.

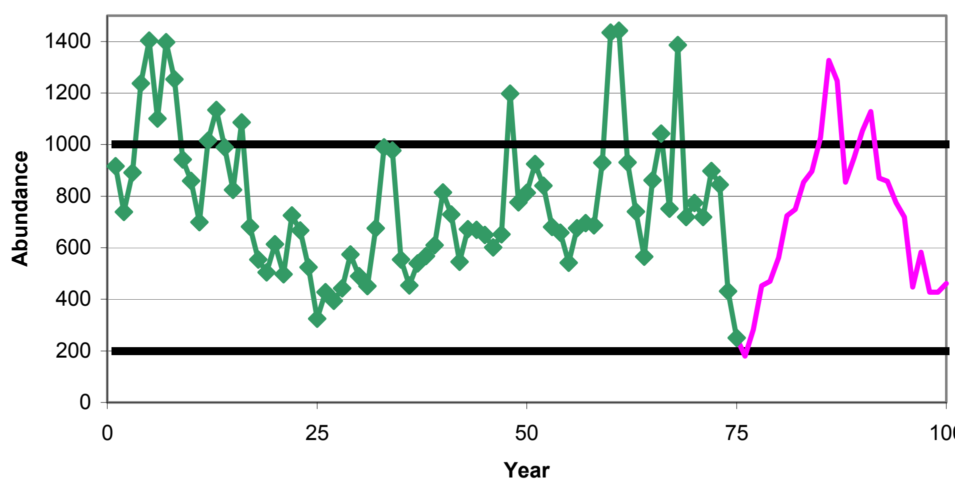


Figure D.4 Simulated trajectory showing the dynamics of the population dynamics model. The upper dashed line represents *k* and the lower dashed line represents *QET*. Once the population goes below *QET*, it is considered functionally extinct, but the trajectory in the diagram continues in order to show the future dynamics had a lower *QET* been selected. Because this is a stochastic model, it is possible for a population to temporarily exceed *k*, but *k* does constrain the upper size of the population.

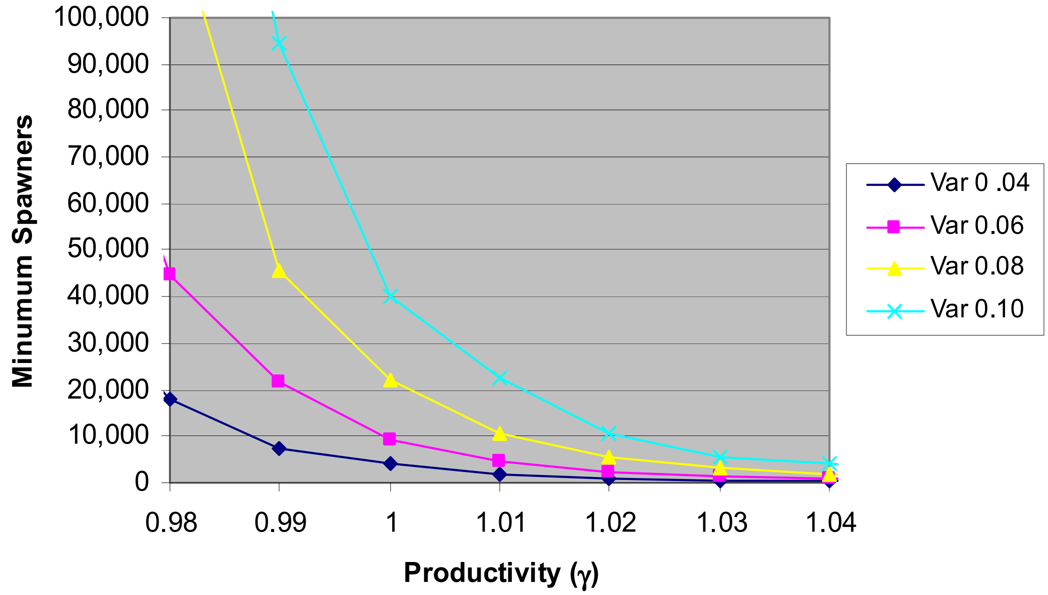


Figure D.5 Viability curves for populations with different values of environmental variability. The acceptable risk is a 5% probability of declining to a four-year average of 50 spawners in 100 years.

Specifying the Acceptable Risk

This criteria approach requires the specification of an acceptable extinction risk. The acceptable risk can be stated as the probability that the population will decline to QET individuals in "time horizon" years. The probability and time horizon parameters are largely policy decisions about acceptable risk, and options regarding these values are presented in this document. The QET should have some biological meaning. This is the population size below which depensitory (Allee) effects are believed to be so strong that extinction risk greatly increases because of processes in addition to environmental stochasticity, or that uncertainty about population behavior becomes unacceptably high (Dennis et al. 1991). This is an extremely difficult parameter to estimate, and the consequences of this parameter estimation problem are discussed below.

Setting QET

Some of the processes that may be important in setting the QET are inbreeding depression, loss of genetic diversity, ecological Allee effects, mate finding, and demographic stochasticity (Goodman 1987, Lande 1998). Of these processes, we set QET at an abundance that avoids potential negative effects from demographic stochasticity and the loss of genetic diversity.

Demographic stochasticity refers to variability in fitness (family size) among individuals, whereas environmental stochasticity refers to environmental variability that affects the mean fitness of the entire population (Lande 1998). The individual variability only tends to affect extinction risk at very small population sizes, because at larger sizes individual variations average out and environmental stochasticity dominates. Demographic stochasticity can lead to increased extinction risk of small populations, because even if the environment is constant, chance variations in family size may result in reproductive failure of all individuals in a single year. Risk from demographic stochasticity is also influenced by chance variations in sex ratio (i.e., there is some probably that only one gender will return). To inform our choice of QET, we explored an individually based simulation model that identified an abundance above which a population is expected to be relatively immune from risks associated with demographic stochasticity caused by variations in family size and chance fluctuations in sex ratio (McElhany and Payne in prep). This model suggested that if a population stays above 40 spawners in a given year, it is likely to experience little additional extinction risk from demographic stochasticity over 100 years. This finding is similar to other studies of risks from demographic stochasticity (Lande 1998).

A number of theoretical and empirical studies relate extinction risk and loss of genetic diversity (e.g., Soule 1980, Thomas et al. 1996, Keller and Waller 2002). As one measure of genetic diversity, the rate of loss of neutral alleles can inform our selection of QET, though it is difficult to make direct links between the loss of neutral alleles and population viability. Published studies on the loss of genetic diversity in small population sizes suggest that at effective population sizes below about 50, there is a relatively high probability of the loss of neutral alleles due to genetic drift (Soule 1980). The effective population size, N_e, is a genetic term referring to number of individuals required if the population had an "ideal" mating system (Wright 1938). The effective size of a population is generally smaller than the census count of the population (Waples 1990a and 1990b) and by assuming an average generation time of five years and an effective population size to census count ratio of 0.2, the Puget Sound Technical Recovery Team developed a recommended QET of an average of 62.5 spawners per year for four years (PS-TRT 2002).

Both the demographic stochasticity and genetic loss approaches suggest that extinction risk is affected by deleterious processes in addition to environmental stochasticity at population sizes below about 50 spawners in a given year. Therefore, we used a QET value of 50 spawners per year for estimating growth rate and abundance viability criteria. This annual spawner count threshold translates to a QET of 200 in the four-year running-sum model (Eq. 1).

Estimating Variance

After the acceptable risk statement is specified, the only parameter used to derive the estimation of the minimum population size for a given productivity is the estimate of environmental variance. Environmental variance is the variance parameter describing the distribution of *r* in equation 1. If we assume that perfect abundance counts are available and that a population is not experiencing density dependence, the variance parameter can be estimated from an abundance time series as (Dennis et al. 1991):

$$\hat{\sigma}^2 = \mathrm{var}\left(\ln\left(\frac{N_{t+1}}{N_t}\right)\right). \qquad \text{Eq. 2}$$

If the population is near some density-dependent carrying capacity, this equation will tend to underestimate the environmental variance parameter in equation 1. Because the recent historical time series used to estimate the environmental variance typically contain large measurement errors, we employed the slope method variance estimation technique developed by Holmes (2001). This method helps correct for the large upward bias in the variance estimate that is produced by measurement error. The slope method equation is:

$$\hat{\sigma}^2 = \text{slope of } \mathrm{var}\left(\ln\left(\frac{N_{t+\tau}}{N_t}\right)\right) \text{vs. } \tau, \qquad \text{Eq. 3}$$

where τ is the temporal lag between the values used for the variance estimate. For our variance estimations, we estimated the slope based on a maximum τ of 4.

The variance estimate is just that, an estimate. Because we assume, based on theoretical and empirical considerations, that $\ln(N_{t+1}/N_t)$ is normally distributed, we have an estimate of the sampling distribution of σ^2. The sampling distribution of the variance of a normally distributed random variable is:

$$\sigma^2 \approx \frac{\hat{\sigma}^2 * df}{\mathrm{X}^2_{df}}, \qquad \text{Eq. 4}$$

where df is the sample degrees of freedom, and X^2_{df} is a chi square distribution with df degrees of freedom (Sokal and Rohlf 1981). If the variance is estimated using perfect abundance counts and equation 2, the degrees of freedom is equal to the number of N_{t+1}/N_t ratios minus 1. If four-year running sums are used, the degrees of freedom would be the number of annual spawner counts minus 4. Variance estimates calculated with the slope method have this same distributional form, but the degrees of freedom are reduced (Holmes and Fagan 2002). Although the slope method reduces bias in the variance estimate associated with measurement error, it does so at a cost of decreased precision. Holmes and Fagan (2002) have calculated tables for determining the degrees of freedom associated with slope method variance estimates.

It is likely that, because of unique circumstances, every population has a unique environmental variance value. However, the variance estimate for any particular population is often extremely uncertain because available time-series data sets are short relative to the levels of variability. If we assume that the populations within an evolutionarily significant unit (ESU) tend to experience similar levels of environmental variation, we can obtain a potentially more accurate and precise estimate of the variance by "pooling" variance estimates from multiple populations. If it is assumed that there is a single true environmental variance value that is common to every population in an ESU and that every population time series represents an independent sample of that variance, the average of all the population estimates provides an unbiased estimate of the true variance, and the sample distribution has the degrees of freedom equal to the sum of the degrees of freedom from each individual population estimate. Under the assumption that all populations experience basically the same levels of environmental variation, the differences in observed variance estimates for individual populations represent a form of sampling error and do not necessarily reflect true differences in variation.

In calculating the minimum population size, we are interested in the natural levels of environmental variation that will be present no matter what hatchery or harvest management strategy is employed. Hatcheries and harvests have the potential to obscure estimates of natural environmental variation if we simply look at number of spawners on the spawning ground. Therefore, in our approach we have incorporated a way of partitioning out the variance changes induced by hatcheries and harvest (McClure et al, McElhany and Payne in prep). We single out hatcheries and harvest for this variance correction process partially because we can measure the effect, but primarily because we have an *a priori* expectation that hatcheries and harvest will alter the level of variation observed on the spawning ground since most harvest strategies explicitly or implicitly seek to reduce variation in escapement and hatcheries are likewise expected to affect observed levels of variance. These variance estimation details are presented in Appendix E.

The variance estimation approach assumes that the historical time series is not experiencing density dependence. If the historical time series represents a population at carrying capacity, then the variance estimate describes the variability in carrying capacity and survival. It is not clear whether this variance estimate would be higher or lower than the variance observed if a population were not experiencing density dependence. If the carrying capacity is fairly stable, the variance estimate calculated for a population near carrying capacity would tend to underestimate the variance of the population abundance below carrying capacity. The power to detect density dependence is generally pretty low (Dennis and Taper 1994, Appendix G this document), which increases our uncertainty about the variance estimate. Given that many populations are declining, it seems reasonable to assume that they are below capacity and are declining, because survivals are too low for replacement; however, the populations could simply be tracking a declining capacity.

Using recent time series to estimate levels of environmental variation for modeling future population dynamics carries the explicit assumption that the recent past will be predictive of future levels of environmental variation (stationarity assumption). Human actions can affect environmental variation, and the future may not resemble the past, but we cannot predict the magnitude or direction of potential change. In general, the viability criteria are determined assuming that the past is a good predictor of future behavior of salmon populations. To the extent that this assumption is violated, the criterion will need to be reevaluated. We obviously will not know the extent to which the assumption is violated until the future happens. It is important to actively test the model's assumptions.

PCC Targets

PCC Targets Overview

If the demographic model and viability curves are going to be employed to establish viability criteria, it is necessary to somehow estimate population productivity. The viability of a population is a function of both the population size and productivity. Therefore, both population size and productivity will need to be evaluated in the future to determine whether currently listed populations have achieved viable status.

The traditional fisheries approach to estimating productivity relies on fitting recent time-series data to stock-recruitment functions such as the Ricker, Beverton-Holt, or hockey-stick models (Hilborn and Walters 1992, Appendix G this document). However, there is generally very little statistical power to estimate productivity with the stock-recruitment model fitting approach (Hilborn and Walters 1992, Appendix G this document). In fact, it is often impossible to even determine whether or not a population has experienced density dependence near capacity over the observed time period (Dennis and Taper 1994, Hooten 1995, Ray and Hastings 1996, Shenk et al. 1998, McClure et al. in review). The conclusion researchers tend to reach regarding whether or not a population is at carrying capacity depends on prior assumptions and on how the question is asked. If the null hypothesis (prior assumption) is that the population *is not* experiencing density dependence, the hypothesis is generally very difficult to disprove. If the null hypothesis (prior assumption) is that the population *is* experiencing density dependence, that hypothesis is also generally very hard to disprove. Accurately and precisely estimating intrinsic productivity is even more challenging than testing hypotheses about carrying capacity because estimating intrinsic productivity requires extrapolation to predict recruitment at very low (i.e., < 1 fish) spawner abundances (Hilborn and Walters 1992). There is seldom much data at these low abundances to support the extrapolations. The extrapolations tend to depend critically on the exact form of the recruitment function employed, and there is often little statistical power to distinguish among different possible recruitment functions (Appendix G). An understanding of the limitations of recruitment curve fitting would be greatly advanced if confidence intervals or probability distributions were commonly reported for parameter estimates of intrinsic productivity, and if formal model selection methods (e.g., Akaike's Information Criterion (AIC)) were adopted. Although in some situations data clearly convey a particular stock-recruitment relationship, they tend to be the exception rather than the rule.

As an alternative to fitting stock-recruitment functions, we have relied on estimates of the population growth rate (observed λ) as a measure of population productivity (γ). The observed growth rate of a population is a precautionary estimate of population productivity, in that the productivity is unlikely to be lower than the observed growth rate, but it may very well be higher. If a population is below carrying capacity, it can grow as a result of increased survival, in which case λ is, by definition, an appropriate estimate of γ (Table D.1). If a population is near carrying capacity, population growth requires an increase in capacity. The γ value for a population tracking an increase in capacity may be expected to be at least equal to its observed growth rate, though it may be higher.

Table D.1 Possible relationships between median annual growth rate and intrinsic productivity.

Observed Median Annual Growth Rate (λ)	**Carrying Capacity (*k*)**	**Intrinsic Productivity (γ)**	**Interpretation**
$\lambda < 1$	$N < k$	$\gamma = \lambda < 1$	Population below carrying capacity and declining because of low survival.
	$N = k$; *k* declining	$\gamma >= 1$; γ may be $> \lambda$	Population tracking a declining carrying capacity.
$\lambda = 1$	$N < k$	$\gamma = \lambda = 1$	Population below carrying capacity and productivity just at replacement.
	$N = k$; *k* stable	$\gamma >= 1$; γ may be $> \lambda$	Population has relatively high intrinsic productivity and is fluctuating around capacity.
$\lambda > 1$	$N < k$	$\gamma = \lambda > 1$	Population below capacity, improvement in survival produces productivity greater than 1. Population will stabilize ($\lambda = 1$) once it reaches capacity.
	$N = k$; *k* increasing	$\gamma > 1$;	Population has relatively high intrinsic productivity and is tracking an increasing capacity.

It is possible to calculate in advance the growth rate associated with a particular change in population size over a specified period of time using the equation

$$\hat{\lambda} = \exp\left(\frac{\ln\left(\frac{\phi}{\iota}\right)}{y}\right). \qquad \text{Eq. 5,}$$

where ι is the initial population size, ϕ is the final population size, and y is the number of years between observations. For example, if a population increased from a four-year average annual abundance of 1,000 spawners to 1,800 in 20 years, the point estimate of λ (= γ) would be 1.033. In addition, the spawner abundance at the end of the 20 years would be 1,800. This ability to estimate productivity associated with a given increase in population size allows for the calculation of the PCC (Figures D.6 and D.7). With PCC, we ask, "Given the current population size, how big does the population need to be in *Y* years to have demonstrated a productivity and abundance that gives an acceptable risk?" This future population size that gives an acceptable risk we refer to as the target size for the population in *Y* years. The target size of a population is a function of the current size of the population, the environmental variance of the population, the acceptable risk statement, and the number of years in which to reach the target. The target size is found using a search algorithm that examines the extinction risk associated with a number of different potential target sizes before identifying the target size with the specified acceptable risk.

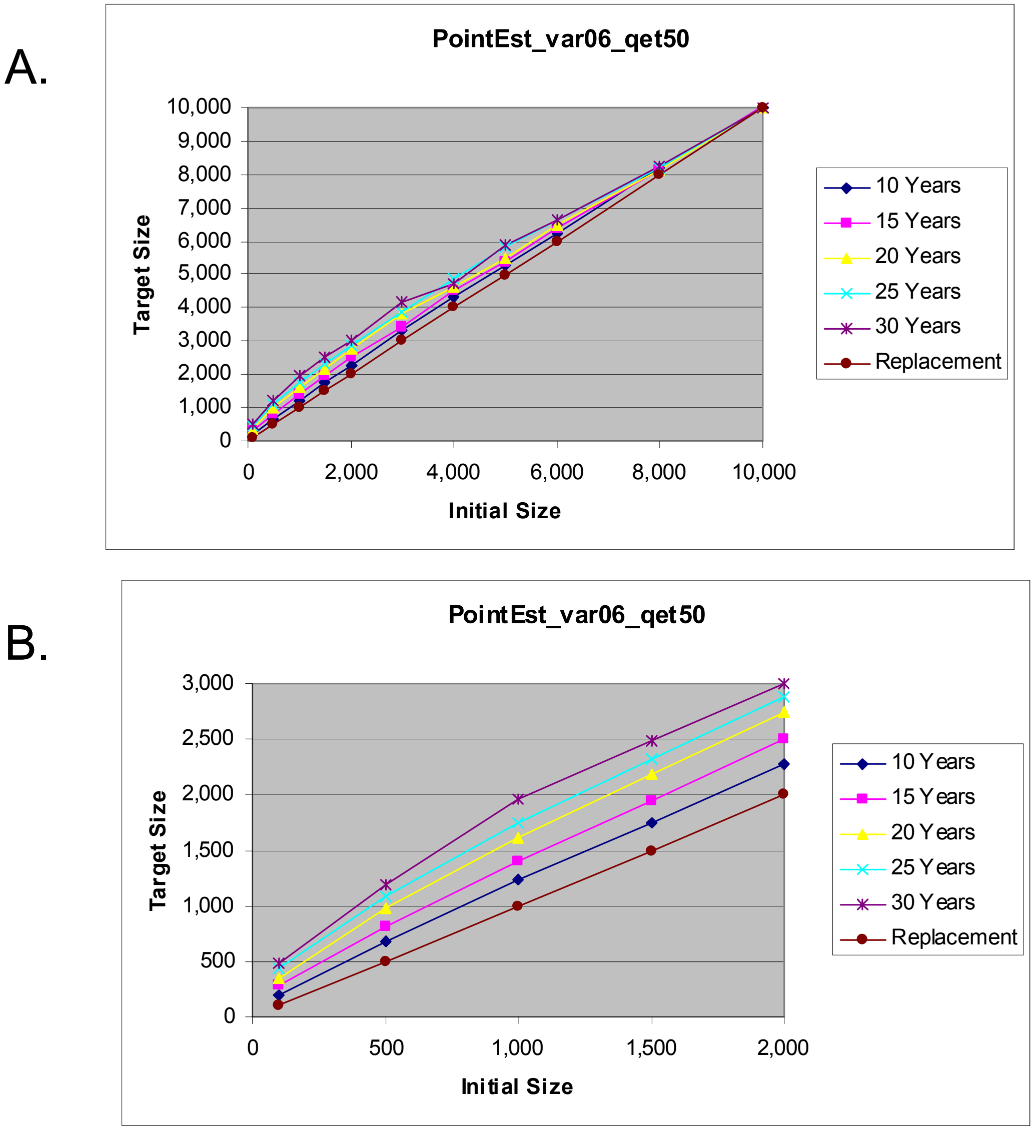


Figure D.6 Population growth criteria based on point estimates of λ and σ^2. The σ^2 value was 0.06. Panel B shows an expansion of the lower portion of the x axis of panel A. The target size is that which a population needs to achieve in a given time to have a productivity ($\gamma = \lambda$) that has an acceptable extinction risk. All curves in the diagram represent a 5% probability of declining to a four-year average of 50 spawners in 100 years. The years in the different curves are the number of years to reach the target size from the initial size. The "replacement" curve is for reference purposes; it indicates where the target size equals the initial size.

The PCC targets may be expressed equivalently as either a target abundance in a given number of years when starting from a given initial abundance (i.e., ϕ in Eq. 5) or as a population growth rate when starting from a given abundance (i.e., $\hat{\lambda}$ in Eq. 5). In this appendix, we report both abundance and growth rate, but in presenting criteria tend to focus on the growth rate targets. Expressing the target as a growth rate emphasizes the key parameter driving the extinction risk evaluation, which is productivity.

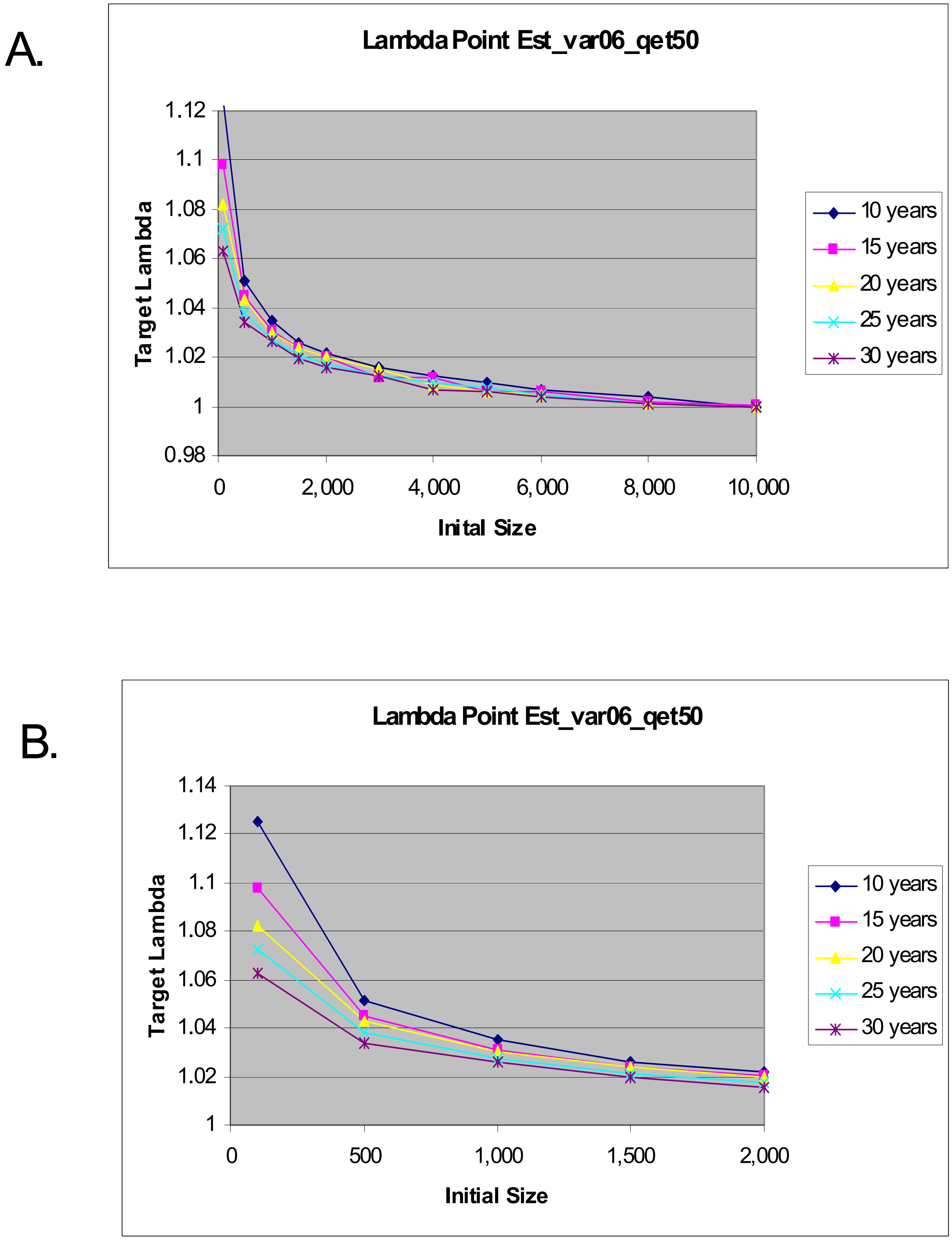


Figure D.7 Growth rates associated with the population change criteria in Figure D.6.

A computer program for calculating PCC based on user input is available at http://research.nwfsc.noaa.gov/cbd/trt/trt_wlc/viability_report.htm.

Parameter Uncertainty in Setting Criteria

There are a number of important assumptions and uncertainties associated with this approach to setting viability criteria. One major source of uncertainty is model uncertainty. Any model is a simplification of reality that attempts to capture the key elements of the problem in order to address specific questions. The appropriateness of the model construct we have used is discussed in the section "Model Uncertainty." In this section, we discuss incorporating uncertainty surrounding parameter estimation in the criteria. In applying the criteria, three parameters are estimated from time series of abundance: σ^2, γ (= λ), and population abundance. The other biologically informed model parameter, QET, is not estimated from the salmon time series.

Because there is natural variability in the system and only relatively short time series are available, there is some probability that the point estimates generated for σ^2 and λ will not reflect the true parameter values. This uncertainty is captured in the parameters' sampling distributions. The sampling distributions of σ^2 and λ can be estimated based on the model assumption that $\ln(N_{t+1}/N_t)$ is normally distributed. The sampling distribution of σ^2 is given in Equation 4 and is a function of the point estimate of the variance, $\hat{\sigma}^2$, and the degrees of freedom for the estimate, which is a direct function of the number of years of data used to calculate the variance estimate. The sampling distribution of λ is:

$$\lambda \approx e^{\mu}, \qquad \mu \approx \hat{\mu} - tinv(df)\sqrt{\frac{\hat{\sigma}^2}{b}}, \qquad \text{Eq. 6}$$

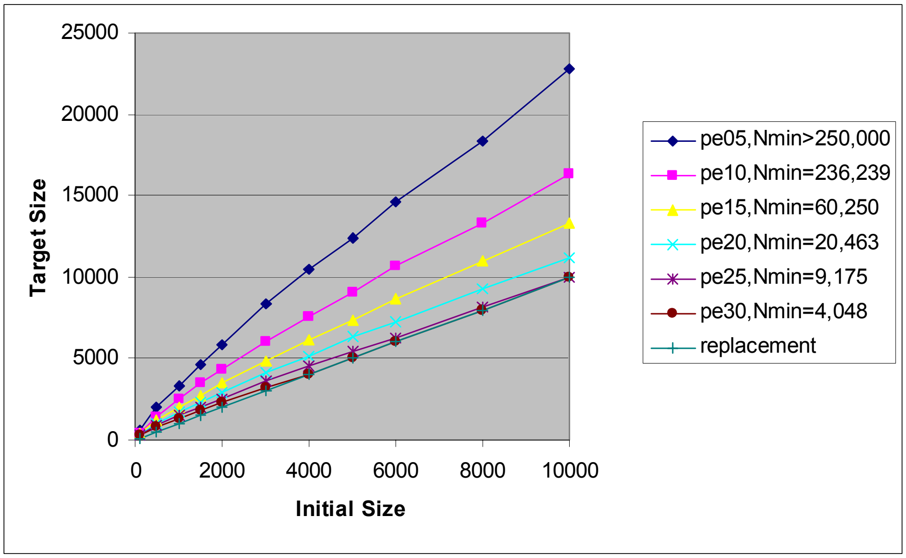
$$\hat{\mu} = mean\left(\ln\left(\frac{N_{t+1}}{N_t}\right)\right), \qquad \text{Eq. 7}$$

$$\hat{\sigma}^2 = \mathrm{var}\left(\ln\left(\frac{N_{t+1}}{N_t}\right)\right), \qquad \text{Eq. 8}$$

where $tinv(df)$ is the inverse t-distribution with df degrees of freedom, df is the degrees of freedom associated with the variance estimate, and b is the number of N_{t+1}/N_t ratios used to calculate $\hat{\mu}$. If the four-year running sum approach is used, b = number of years of spawner counts minus 4. Note that the time series used to estimate $\hat{\sigma}^2$, does not need to be identical to the time series used to estimate $\hat{\mu}$, and the df associated with the sampling distribution is functionally independent of the b parameter. This allows the use of the variance estimate and degrees of freedom associated with the pooled variance estimate in determining the sampling distribution of λ (see Appendix E). The b parameter will be a function of the number of years needed to achieve the target.

Because there is uncertainty in the parameter estimates, the true probability of extinction is not simply the fraction of time the population with point estimate σ^2 and γ values is expected to go extinct. There is some probability that the true σ^2 value is higher than $\hat{\sigma}^2$ and/or that the true μ is lower than $\hat{\mu}$, in which case the probability of extinction would be higher than that

A.



B.

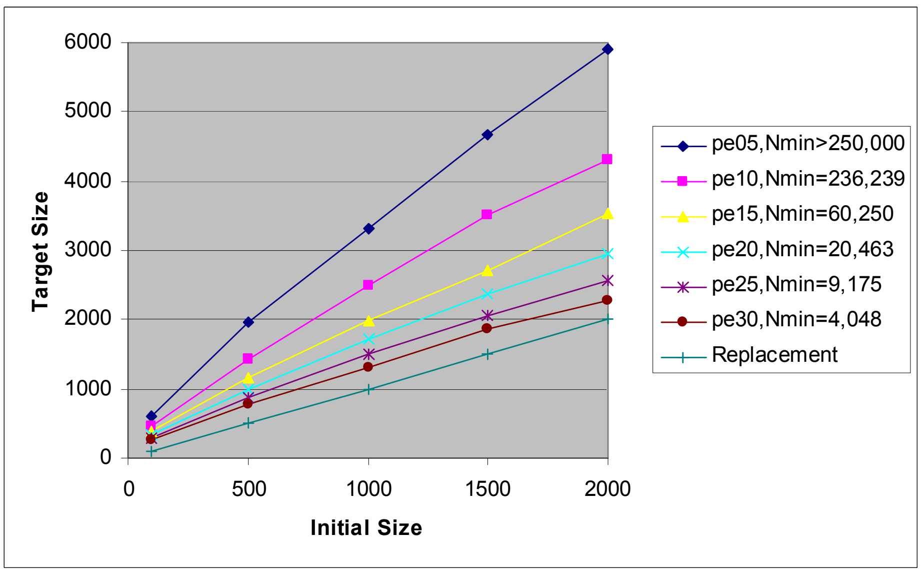
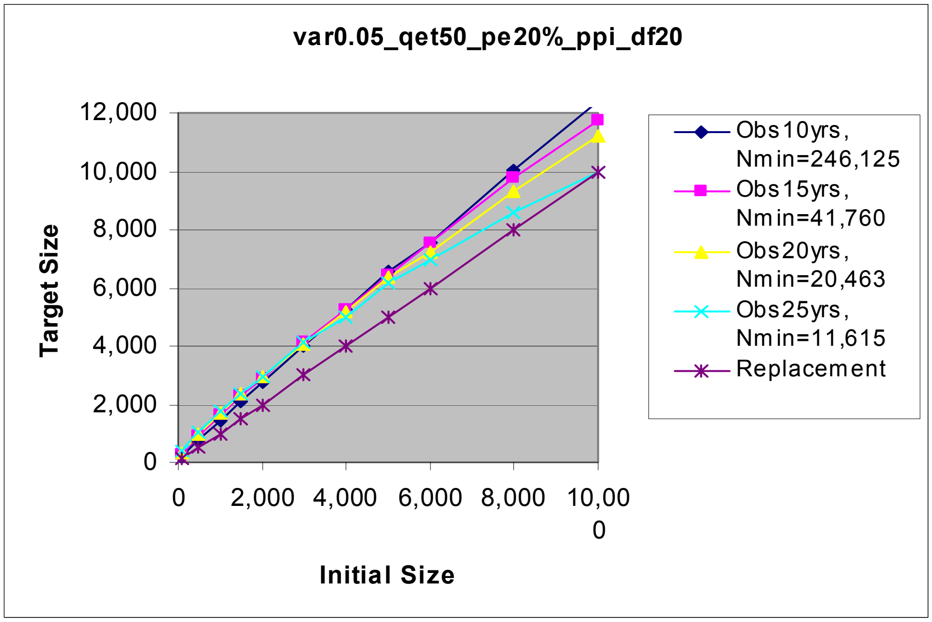


Figure D.8 Population growth criteria based on population prediction intervals. The point estimate of σ^2 is 0.05. The degrees of freedom for the variance estimate was given as 20. The different curves represent different probabilities of declining to a four-year average of 50 spawners in 100 years. The time to reach the target size is fixed at 20 years. The Nmin values in the figure key show the abundance at which the target size is equivalent to the initial size. For any abundance above this Nmin value, the population simply needs to show the same four-year average abundance after 20 years as the initial size. Panel B shows an expansion of the lower portion of the x axis of panel A. The "replacement" curve is for reference purposes; it indicates where the target size equals the initial size.

estimated by the parameter point estimates. Likewise, there is some probability that the true σ^2 value is lower than $\hat{\sigma}^2$ and/or that the true μ is higher than $\hat{\mu}$, in which case the probability of extinction would be lower than that estimated by the parameter point estimates. To account for this uncertainty, we calculated the population prediction intervals to establish the PCC targets (Figures D.8 through D.10).

A.



B.

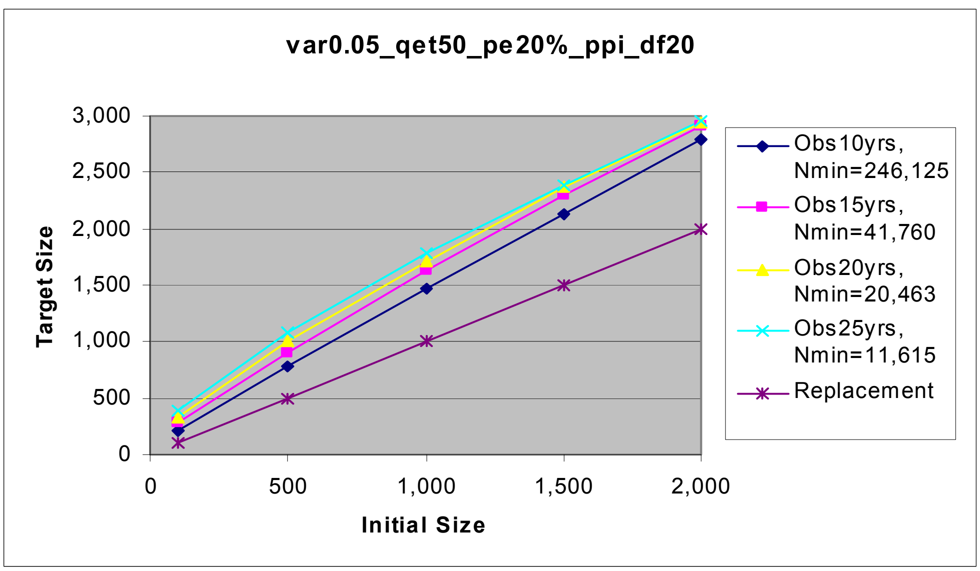


Figure D.9 Population change criteria showing the effect of different values of the time to reach the target. The criteria are based on population prediction intervals. The variance is 0.05 with 20 degrees of freedom, and the acceptable risk is a 20% probability of declining to a four-year average of 50 spawners in 100 years. Panel B shows an expansion of the lower portion of the x axis of panel A. The “replacement” curve is for reference purposes; it indicates where the target size equals the initial size.

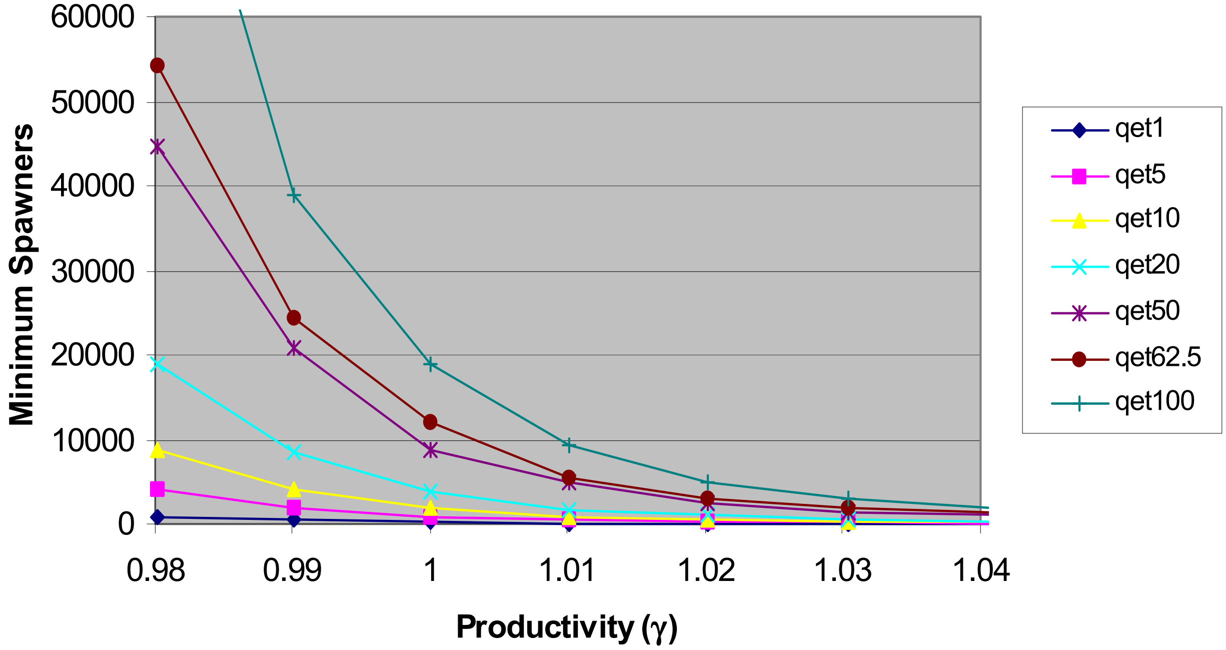


Figure D.10 Point estimates of λ associate with reaching the PPC in Figure D.9.

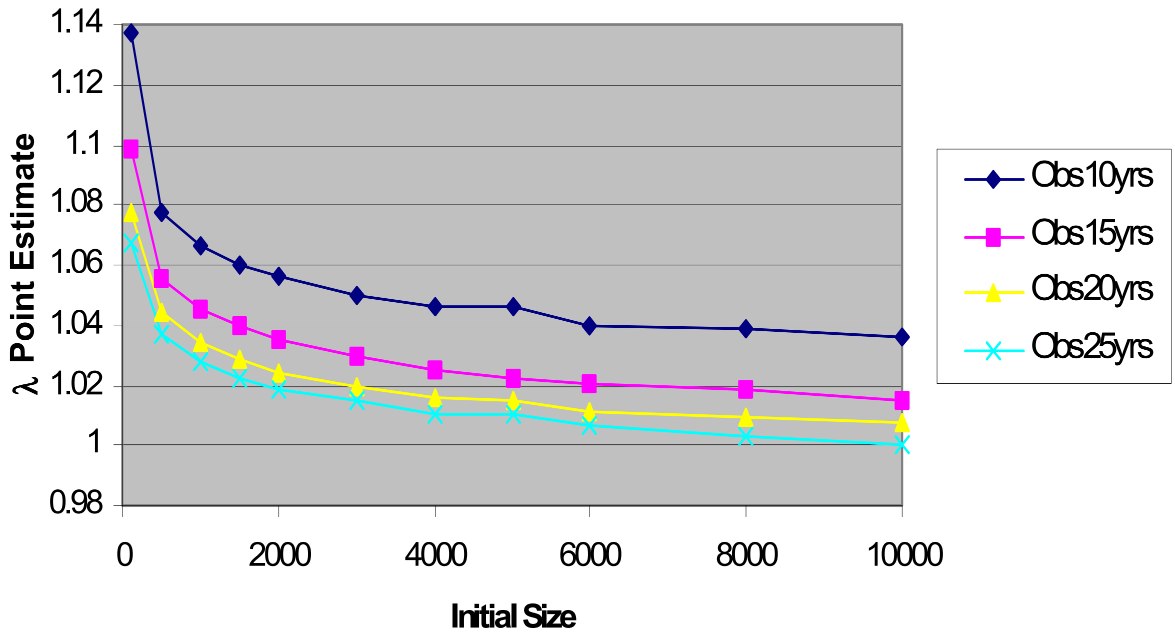
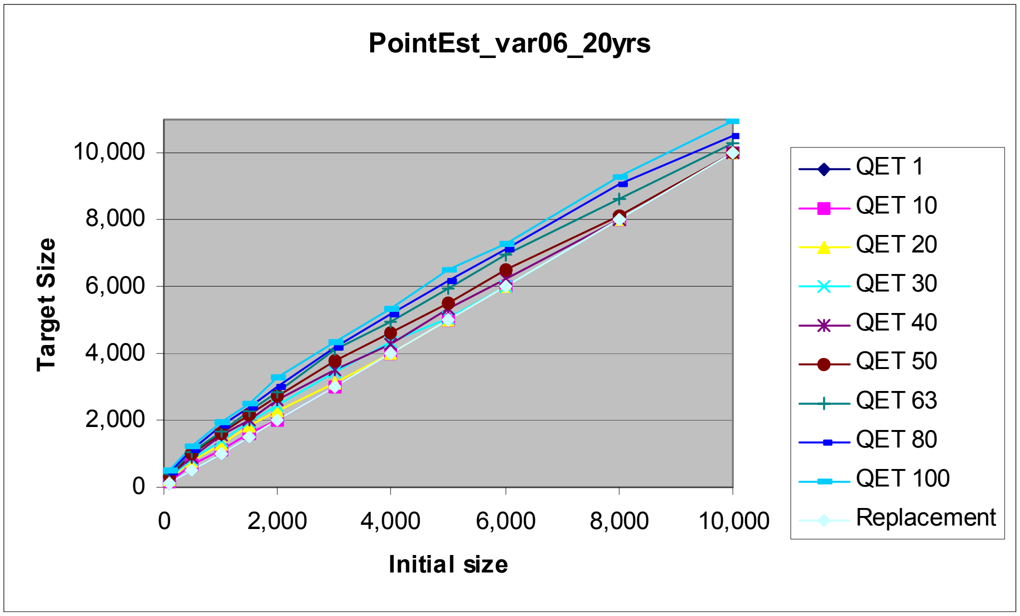


Figure D.11 Viability curves for different values of QET. The variance is 0.06, and the acceptable risk is a 5% probability of declining to a four-year average of QET spawners in 100 years. Note that as the productivity increases, the difference in minimum size associated with different QET values decreases.

A.



B.

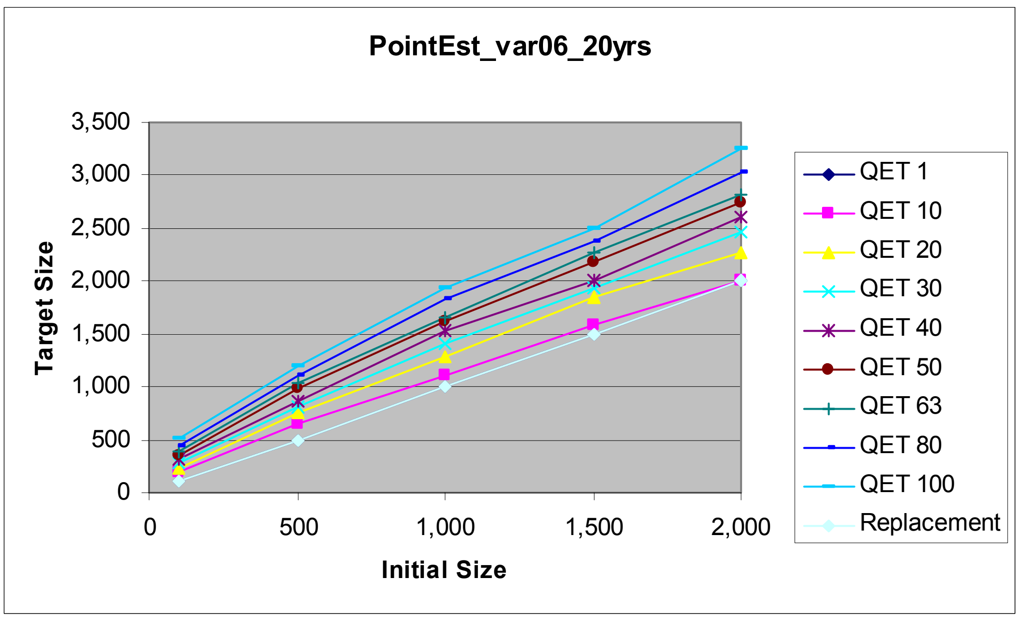


Figure D.12 Population change criteria showing for different values of QET. The criteria are based on point estimates. The variance is 0.06 and the acceptable risk is a 5% probability of declining to a four-year average of QET spawners in 100 years. The time to reach the target is fixed at 20 years. Panel B shows an expansion of the lower portion of the x axis of panel A. The "replacement" curve is for reference purposes; it indicates where the target size equals the initial size.

trajectories that drop below QET within the specified period of time (e.g., 100 years). Rather than parameterize the model simply using the point estimates, the γ and σ^2 parameters are drawn independently and randomly from the appropriate sampling distributions. This approach has been referred to in the literature as population prediction intervals, parametric bootstrapping, or simply a type of Monte Carlo simulation. Figures D.6 and D.8 compare extinction risks calculated with point estimates and risks calculated using population prediction intervals. When we incorporate the uncertainty associated with parameter estimation into our assessment of extinction risk, we generally require larger target population size for a given acceptable level of risk. Original guidance from NMFS identified an acceptable population extinction risk of a 5% probability of extinction in 100 years for a VSP.

In order to evaluate the status of a population relative to the criteria, it is also necessary to estimate its abundance at the initial and target time periods. The time series of abundance is not informative regarding the accuracy of the abundance estimates. To access uncertainty about the abundance estimates, it is necessary to know something about the measurement and sampling error associated with the count method. The WLC-TRT has not yet evaluated the errors associated with different abundance estimates; we assume that the initial and target abundances are measured precisely and without bias. As future studies evaluate the accuracy of abundance counts, the target sizes may need to be adjusted to achieve the same level of certainty about the population extinction risk.

The QET is a biological parameter that is not estimated from salmon data. The only way we can incorporate uncertainty about QET into our criteria assessment is through sensitivity analysis (Figures D.11 and D.12). In sensitivity analysis, we explore the effect of changing the assumption about QET on the proposed criteria. As the γ value increases, the effect of QET declines.

Hatcheries and PCC Targets

In assessing viability, we are concerned with the question of whether a population would be naturally self-sustaining. Hatchery-origin fish that spawn with natural-origin fish have the potential to "mask" the productivity of the wild population (McClure et al. in review). The equation for estimating the growth rate used to calculate the PCC target of a population with hatchery-origin fish is:

$$\hat{\lambda} = \exp\left(mean\left(\ln\left(\frac{N_{t+1}}{N_t + hN_t} \right) \right) \right) = \exp\left(\frac{\ln\left(\frac{\phi}{\iota} * (1-\eta)^b \right)}{y} \right), \qquad \text{Eq. 9}$$

where N_t is the number of natural-origin spawners in year t, hN_t describes the effective number of hatchery-origin fish spawning in year t as a function of N_t, ϕ is the target number of natural-origin spawners, ι is the current number of natural-origin spawners, η is the effective proportion of the spawning population of hatchery origin, and y is the number of years between observations. The effective proportion of hatchery-origin spawners may be different from the census count proportion of hatchery-origin spawners if hatchery-origin fish have a different reproductive success than natural-origin spawners. The fraction of hatchery-origin spawners is the fraction anticipated over the target period. Figure D.13 shows the effect of changing the fraction of hatchery-origin spawners. A relatively small fraction of hatchery-origin spawners can have a big impact on the target size needed to demonstrate a given level of productivity. To

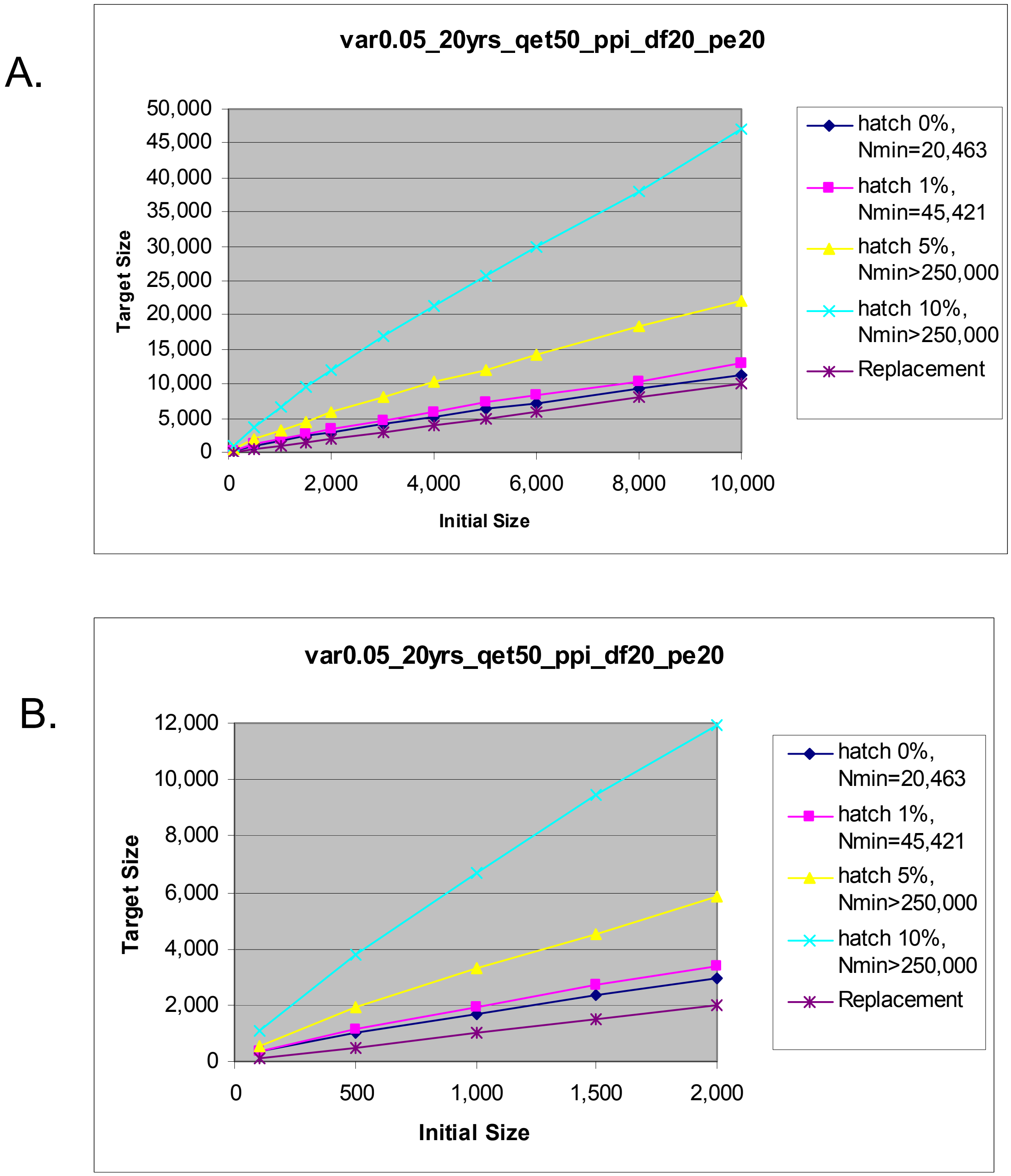


Figure D.13 Population change criteria showing the effect of different fractions of hatchery-origin spawners. The criteria are based on population prediction intervals. The variance is 0.05 with 20 degrees of freedom and the acceptable risk is a 20% probability of declining to a four-year average of 50 spawners in 100 years. Panel B shows an expansion of the lower portion of the x-axis of panel A. The "replacement" curve is for reference purposes and indicates where the target size equals the initial size.

evaluate the productivity of a population with hatchery-origin spawners, it is necessary to have an accurate estimate of the effective fraction of hatchery-origin fish.

Ocean Cycles

The population dynamics model described in Equation 1 assumes no temporal autocorrelation in productivity. However, salmon are recognized as experiencing decade-scale periods of higher- or lower-than-average productivity as a result of long-term cycles in ocean conditions (Mantua et al. 1997, Anderson 1998, Beamish et al. 1999, Hare et al. 1999). These long-period "regime shifts" are difficult to model because they are difficult to predict. However, they can have significant consequences for setting and evaluating performance of viability criteria. It is important to not conclude that population is viable during a period of high marine survival if it can be anticipated that the population is likely to go extinct during the next period of low marine survival. Likewise, we would not want to conclude that a population is not viable during a period of low ocean survival if it can be anticipated that the long-term prospects for the population are good, given that it is likely to soon enter a period of higher ocean survival. These issues are illustrated in Figure D.14. We partially address this concern about ocean cycles by including juvenile outmigrant (JOM) criteria, which attempt to separate out the freshwater and marine survivals. However, we also considered marine cycles in setting adult abundance viability criteria.

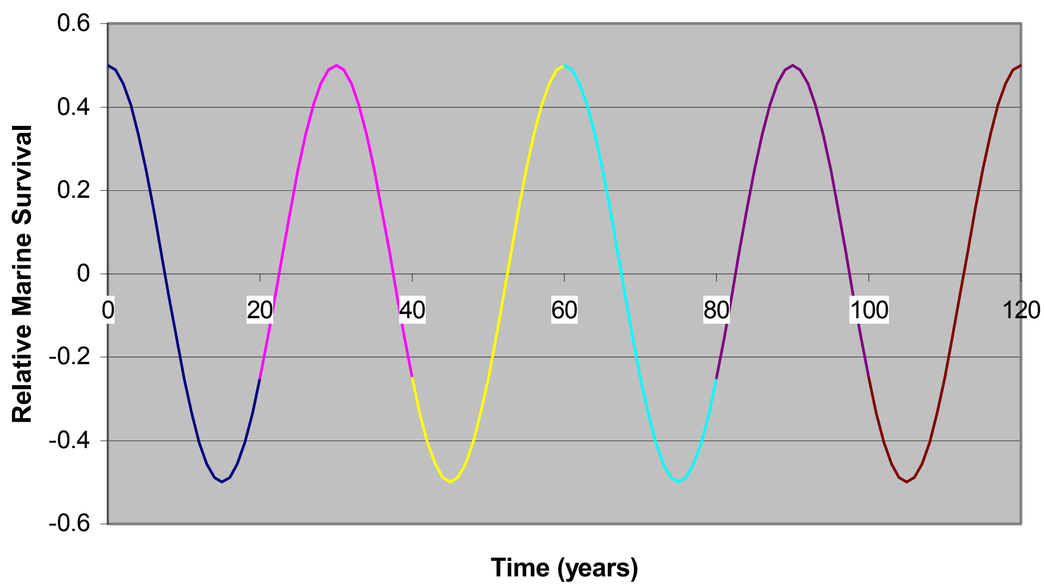


Figure D.14 Conceptual graph of 30-year marine survival cycles. Different colors in the curve represent different potential periods over which the target is achieved. Each potential observation period would have different marine index ratios. Real marine survival patterns are not nearly as predictable as this sine wave.

Given that it is difficult to predict patterns of marine survival, we took the approach of modifying the target criteria as a function of how the marine survival over the target period compared to the long-term average marine survival (Figure D.15). The modification, applied to the calculation of λ over the target period, is as follows:

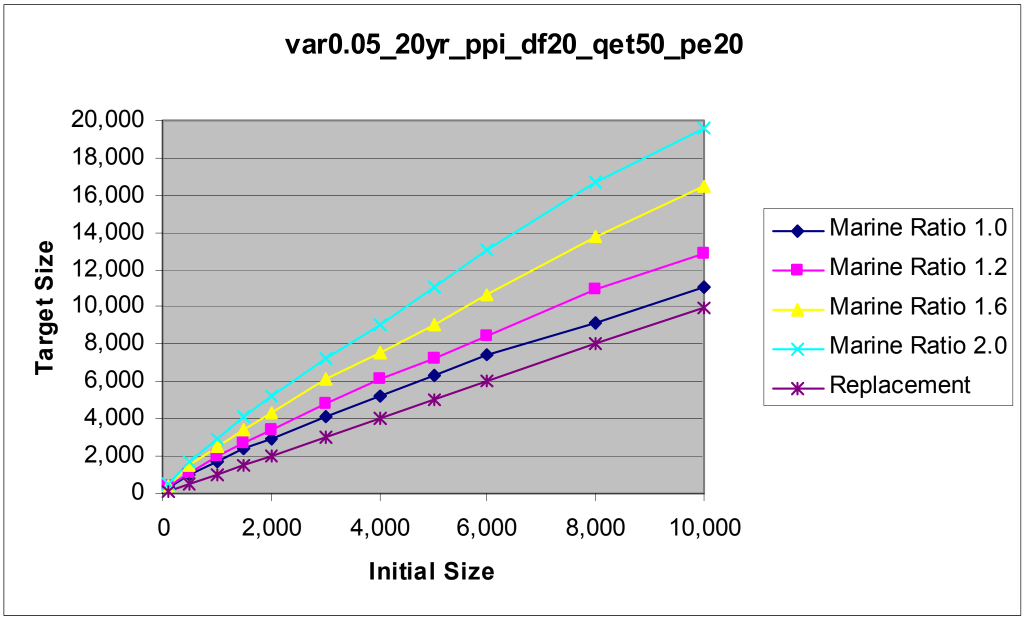
$$\hat{\lambda} = \exp\left(\frac{\ln\left(\frac{\phi}{\iota}\right)}{y} - \frac{\ln\left(\frac{\nu}{\theta}\right)}{y} \right), \qquad \text{Eq. 10}$$

where ν is the marine survival index observed over the target period, θ is the long-term average value of the same marine survival index and all other symbols are as in Equation 5. A basic assumption of this approach is that the target values calculated without the correction represent the minimum sizes based on some long-term average growth rate. When we apply the correction, we assume that the observed growth rate differs from the long-term average growth rate in an amount that is proportional to the difference between the observed marine index and the long-term average marine index. Since there is logically a direct relationship between ocean survival and productivity throughout the life cycle, this a reasonable assumption.

In developing the viability criteria, we applied this correction asymmetrically; that is, the modification is only used to increase the target during periods of high ocean survival, not to reduce the target during periods of low ocean survival. This is a precautionary application. If we observe a population with a marine survival over the target period that is higher than long-term average, we are relatively certain that at some future time the marine survival will decrease; thus we should stipulate a higher target during the "good" ocean years. The converse is not necessarily true. If we observe a lower than long-term average marine survival over the target period, it is not clear that marine survival will improve. This is because human activities—such as those that affect global warming—may have permanently reduced ocean productivity for salmon, or the condition of fish as they leave freshwater may be the cause of the low marine survivals. For these reasons, we did not lower the abundance target during periods of low ocean survival.

We have not yet identified the appropriate index (assuming one exists) to use for this marine survival modification to the target criteria. Several candidates exist, including measures of marine survival estimates from hatchery-marked fish or physical indexes such as the Pacific Decadal Oscillation (PDO) or El Niño-Southern Oscillation (ENSO), which are correlated with salmon marine survival. Although many features of this marine index approach are conceptually attractive, whether it can be satisfactorily implemented remains to be seen.

A.



B.

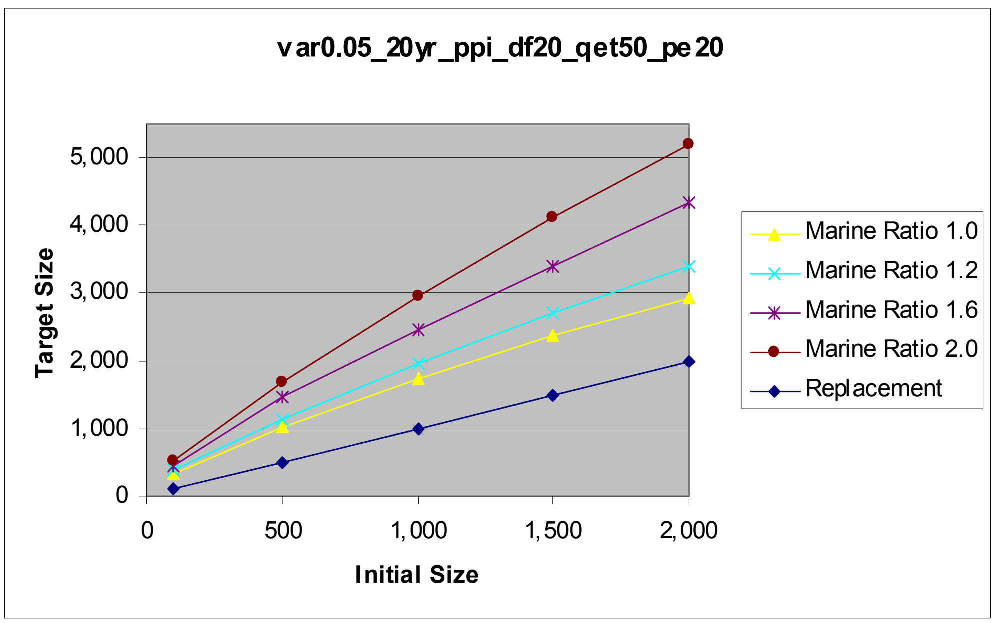


Figure D.15 Population change criteria showing the effect of marine survival modification. The marine ratio is the marine survival index observed over the target period divided by the long-term average marine index. The criteria are based on population prediction intervals. The variance is 0.05, with 20 degrees of freedom, and the acceptable risk is a 20% probability of declining to a four-year average of 50 spawners in 100 years. Panel B shows an expansion of the lower portion of the x axis of panel A. The “replacement” curve is for reference purposes; it indicates where the target size equals the initial size.

Model Uncertainty

We address model uncertainty by evaluating how well the criteria performed when confronted with simulated time series abundance data that was generated using processes other than those used to set the criteria (McElhany and Payne in prep.)(Figure D.16). For example, we generated a large number of trajectories with different recruitment functions (e.g., Ricker, Beverton-Holt), short-lag autocorrelations, decadal-scale regime shifts, and changes in population carrying capacity. We then calculated viability criteria using the early part of the simulated time series, determined the conclusion we would reach about the population after applying the criteria to the next segment of the time series, and finally looked at the long-term fate of the simulated population to determine whether our conclusions were correct. For every scenario tested we generated a table like Table D.2 to examine the rate at which the criteria lead to certain types of errors. The criteria tested by McElhany and Payne are not identical to the

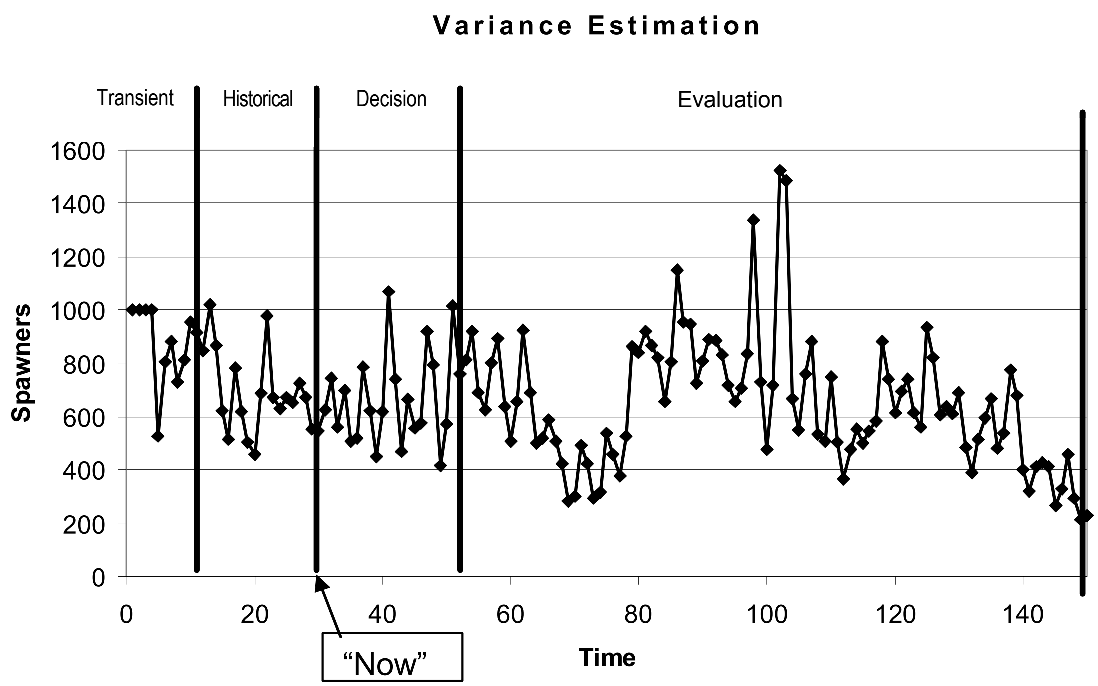


Figure D.16 Sample trajectory illustrating the approach used to evaluate the viability criteria showing variance estimation, decision, and evaluation period. The first 10 years, during which initial transients in the age structure were allowed to stabilize, was not used for estimation or evaluation. The variance estimation period was used to estimate process variance and set the viability curve. The variance estimation period overlapped with the decision period. In most of our simulations, we assumed that it included a period of historical data and was updated to include data from the decision period. The decision period was used to estimate the growth rate and reach a decision about whether or not to delist the population. The evaluation period was used to explore the fate of the simulated population after the delisting decision was made.

Table D.2 Possible outcomes of criteria applied to simulated trajectories.

		Delisting Decision	
		Delist	Do Not Delist
Population fate	Extinct	Type I error	Correct
	Not extinct	Correct	Type II error

criteria presented in this report (for example, the marine index modification is a recent addition to the criteria), but the criteria in the drafts are very similar, and the general conclusions are appropriate to both. In general, the criteria were robust to the exact function of the population dynamics model (e.g., Ricker versus hockey-stick recruitment function, presence of short-lag autocorrelation, etc.). As expected, the criteria lead to the wrong conclusion most often when the population is starting at carrying capacity and has a high intrinsic productivity. Under these conditions, a population has a relatively low risk of extinction, and the criteria tended to be overly precautionary by not recognizing the populations as viable. Given the low current abundance of most populations, it is anticipated that most populations will need to grow to be considered viable, and this overly precautionary scenario will be the exception rather than the rule.

Minimum Targets

The PPC approach is appropriate once the initial population size is above a certain level, but it does not work well at extremely small initial sizes. For example, we cannot use the approach to set a target for a currently extirpated population. The analysis requires evaluating the term *targetSize*/*initalSize*. Since *initialSize* for an extirpated population is 0, the term is undefined, and no target size can be identified. Even if we have a non-zero initial size, so that the equations are solvable, there is still a difficulty at small population size. If the initial size is one fish and the population increases to 50 fish over 20 years, the growth rate for the population is large (λ = 1.28, or a 28% increase per year), and because of the large growth rate, a population size of 50 may exceed the minimum size requirement for an acceptable risk (this is a function of the variance and QET). However, 50 fish may not be considered adequate target abundance for a number of reasons. One primary reason is because the proportional error rates in abundance estimates tend to be higher at small abundance (Holmes and Fagan 2002). Therefore, an estimate of productivity made at small population size is more likely to be wrong than an estimate made at higher population size. Consequently, we developed a set of minimum targets that should be met no matter how low the initial estimate of abundance. These minimum targets are based on setting a minimum initial population size that will serve as the basis for target criteria for all populations starting below the minimum initial size. Because of the uncertainty concerns, we have explored a number of values as the minimum initial size. If a population is below the minimum default value and achieves the targets for a population with an initial size of the minimum default value, the population will actually have a higher point estimate productivity than would be required if the criteria algorithm were simply applied at the low abundance.

Alternative Methods of Estimating Productivity

The population change criteria provide a precautionary and statistically defensible approach to estimating the intrinsic productivity of a population. However, in some cases it may not be necessary to directly observe population growth in order to conclude that a population has a productivity-size combination with an acceptably low risk level. If a population demonstrates a productivity-size combination above the appropriate viability curve, the population would be considered viable.

As discussed in Appendix G, fitting recruitment models to abundance data generally provides poor estimates of intrinsic productivity, but in particular cases data may support the use of this method. Appendix H describes a particular two life-stage recruits-per-spawner model. Information available for harvested populations may provide additional data to evaluate the productivity of a population. Given certain assumptions about natural levels of post-harvest mortality, it may be possible to estimate something about the “resilience” of a population (though not necessarily its intrinsic productivity). Calculations involving harvest would need to have an accurate method of assessing the harvest rate actually experienced by a particular population. In addition, an accurate accounting of hatchery fish in the system would be required to estimate natural productivity.

To be used to evaluate the viability of a population, any alternative method of estimating population productivity would need to meet reasonable standards of statistical rigor. The potential use of alternative methods to estimate productivity does not really aid in specifying, *a priori,* a particular point on the viability curve to use as a target. Rather, the alternative methods may be used to retrospectively evaluate whether or not a population should be considered viable.

Application of Population Change Criteria to Healthy Populations

The PCC approach is only applicable for evaluating whether or not a population that has been depressed below its historical abundance has improved in status and should be considered viable. If a population has not been depressed below its historical abundance, it would not be expected to grow in the future. If a population is not growing, the PCC approach assumes that the population productivity is 1. Abundance targets associated with a productivity of 1 are often larger than estimates of historical abundance. We would intuitively categorize a population that is stable at about its historical abundance as “healthy” because we are assuming, perhaps unconsciously, that the population productivity is actually greater than 1, and that the population is not growing because it is constrained by carrying capacity. If a population is stable at about historical abundance, we may not require further evidence about its productivity to conclude that it is viable. Alternatively, we may be able to apply one of the alternative methods for estimating productivity described in the previous section.

Most Willamette/Lower Columbia (WLC) populations are substantially below historical abundance and are not considered currently healthy, hence the Endangered Species Act (ESA) listing. Even the most abundant population, the Lewis River bright chinook salmon population, at its most recent four-year annual average of 8,900 spawners, is well below the historical estimate of equilibrium abundance based on habitat productivity viability analysis (HPVA) of 43,000 spawners. Even given the uncertainties associated with the ecosystem diagnosis and treatment (EDT) estimates, it seems likely that there is, at least theoretically, potential for the population to grow.

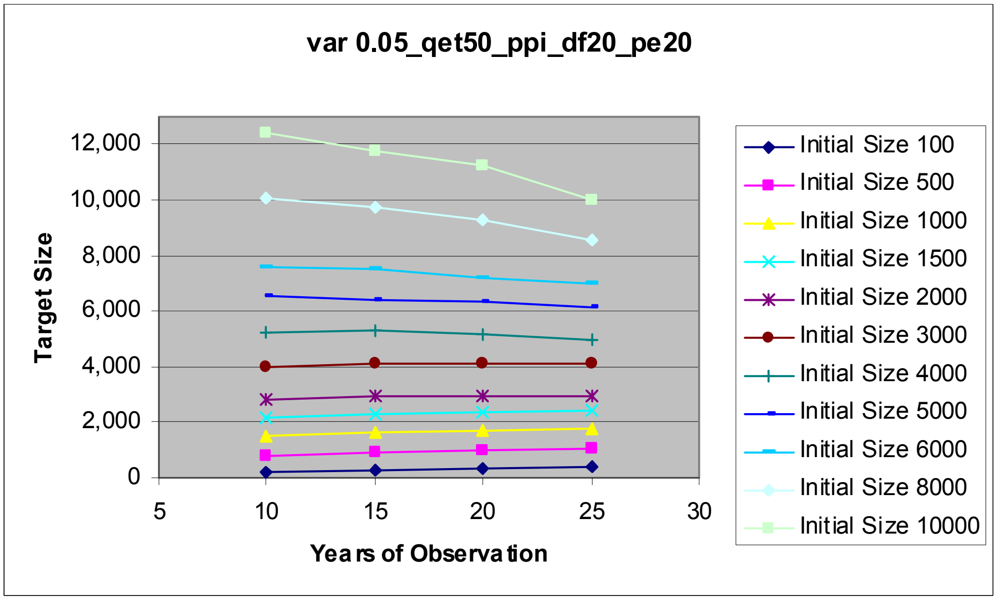
Evaluation Time Period

Power analyses indicate that at least 12 years of data are required before λ estimates have any meaning (Holmes 2001, Holmes and Fagan 2002, McElhany and Payne in prep, McClure et al. 2003). While we have shown 10-year observation periods for illustration purposes, 10 years is really too short; 15 to 20 years is more appropriate, both in terms of estimating growth rate and averaging over a longer portion of any marine survival cycles (Figures D.6, D.7, and D.17). However tempting it may be to conclude that a population is okay if it achieves the target abundance before 15 to 20 years, it is crucial to recognize that such a conclusion would be statistically unsound. The criteria are based on variability patterns, and it is necessary to wait and see if the population is still above the target size after the target time. Even a declining population may momentarily exceed the target size, and it is the long-term behavior of the population that is relevant.

An important question in applying these criteria is when to start evaluating population status. One strategy is to simply start with the current population size and look forward. Alternatively, we can stipulate that any time series of acceptable length that meets the criteria and includes the most recent year's data would qualify as viable. While the later option may be possible in some populations, for many of them there is simply no credible historical time series available: starting from the present and looking forward is the only option. Given the sensitivity of the criteria to small changes in the fraction of hatchery-origin spawners, it becomes even more unlikely that historical data are adequate. However, it is possible to include data before 2002 in assessing the status of populations if the data are of sufficient quality.

It is not possible to entirely stipulate the criteria in advance because they depend on evaluating marine survivals over some future period. Although the projected fraction of hatchery-origin spawners can be estimated, it too will need to be actually evaluated to determine if the abundance target is adequate. As part of an adaptive management protocol, the variance estimates should also be updated as more data become available.

A.



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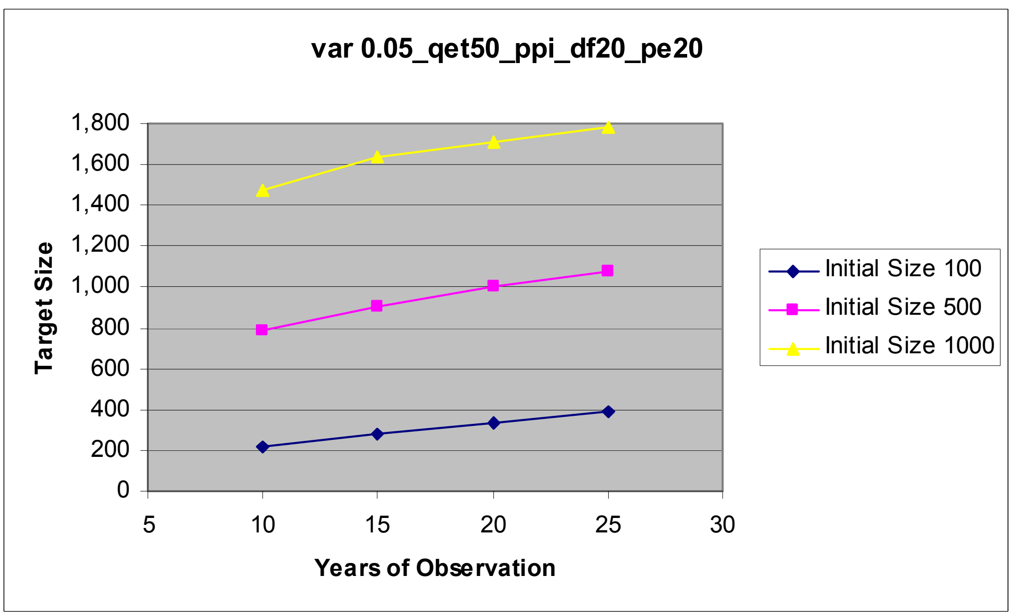

Figure D.17 Target size as a function of the number of years to reach the target for a number of different initial population sizes. The criteria are based on population prediction intervals. The variance is 0.05 with 20 degrees of freedom, and the acceptable risk is a 20% probability of declining to a four-year average of 50 spawners in 100 years. Panel B shows an expansion of the lower portion of the y axis of panel A.

PCC Criteria in the WLC

Current Abundance and Hatchery Fraction

PCC targets (either growth rate or abundance) assume a variety of conditions, which can be found in Tables D.3 and D.4. An appropriate target could be determined from Table D.3 or D.4 if the current population size (Table D.5) and the other model parameters are known. The current population sizes for many WLC populations are found in Table D.5. The table also contains the recent fraction of hatchery-origin spawners for some populations, which could be used in conjunction with Table D.3, assuming that the current fraction of hatchery-origin spawners will continue into the future. However, hatchery production is under human control, and the future fraction of hatchery-origin spawners will reflect future policy decisions.

Variance Estimates

The key empirical parameter for setting the criteria is the estimate of environmental variance. Variance estimates for populations in the WLC domain are summarized in Appendix E. The Lower Columbia ESUs have average variance point estimates of about 0.05; a value of 0.05 was used to generate criteria for these populations. In general, the variance estimates (and targets) will need to be evaluated as more data become available.

Final PCC Recommendations

This appendix is intended to describe and illustrate the PCC approach by example. The final WLC-TRT recommendations regarding the PCC criteria are located in the main text of this document. The final recommendations include a discussion of when it would be appropriate to use the PCC approach as viability criteria and when other methods should be used.

Table D.3 Sensitivity analysis of PCC targets. Targets are expressed as observed, median, annual population growth rates, assessed on a four-year running sum.

Current Size	Standard[a]	Time Period 40[b]	Variance[c] .01	Variance[c] .1	Variance Degrees of Freedom[d] 5	Variance Degrees of Freedom[d] 10	Variance Degrees of Freedom[d] 40	Hatchery Fraction[e] 5%	Hatchery Fraction[e] 10%	Hatchery Fraction[e] 30%	QET[f] 100	Extinction Risk[g] 1	Extinction Risk[g] 25	Extinction Risk[g] 60	Acceptable Time Horizon 200[h]	Marine Index Long-Term[i]
100	12%	7%	4%	18%	16%	13%	11%	16%	>21%	>21%	14%	16%	7%	4%	13%	13%
150	11%	6%	4%	17%	15%	12%	10%	15%	20%	>21%	13%	15%	6%	2%	12%	12%
200	11%	6%	3%	16%	15%	12%	10%	15%	20%	>21%	12%	14%	5%	1%	12%	12%
500	9%	5%	3%	14%	12%	10%	9%	13%	19%	>21%	10%	13%	4%	-1%	11%	10%
1,000	8%	4%	2%	13%	11%	9%	8%	12%	18%	>21%	9%	12%	2%	-2%	10%	10%
1,500	7%	4%	1%	12%	10%	8%	7%	12%	17%	>21%	8%	12%	2%	-3%	9%	9%
2,000	7%	4%	1%	12%	10%	7%	7%	12%	17%	>21%	8%	12%	2%	-3%	9%	8%
2,500	7%	3%	1%	12%	10%	8%	6%	11%	16%	>21%	8%	11%	2%	-3%	9%	9%
3,000	6%	3%	1%	12%	9%	7%	6%	11%	16%	>21%	7%	11%	1%	-3%	9%	8%
3,500	7%	3%	0%	11%	9%	7%	6%	11%	16%	>21%	7%	10%	1%	-4%	9%	8%
4,000	6%	3%	0%	11%	9%	7%	6%	11%	16%	>21%	7%	11%	1%	-4%	9%	8%
4,500	6%	3%	0%	11%	9%	7%	6%	11%	16%	>21%	7%	10%	1%	-4%	9%	8%
5,000	6%	3%	0%	11%	8%	7%	6%	11%	16%	>21%	7%	10%	1%	-4%	9%	8%
6,000	6%	3%	0%	11%	9%	6%	5%	10%	16%	>21%	7%	10%	0%	-4%	9%	7%
7,000	6%	3%	0%	11%	8%	6%	5%	10%	15%	>21%	6%	10%	0%	-5%	8%	7%
8,000	5%	2%	0%	10%	8%	6%	5%	10%	15%	>21%	6%	11%	0%	-5%	8%	7%
9,000	5%	2%	0%	10%	8%	6%	5%	10%	15%	>21%	6%	10%	0%	-5%	8%	7%
10,000	5%	2%	-1%	10%	8%	6%	5%	10%	15%	>21%	6%	10%	0%	-5%	8%	7%

[a] This column describes the targets assuming standard conditions: for these analyses, they were a 20-year observation period, process variance of 0.05, 20 degrees of freedom for the variance estimate, 0 hatchery-origin spawners, a QET four-year average of 50 spawners per year, and an acceptable extinction risk of 5% in 100 years. The other target columns show target calculated by varying one of the standard assumptions and keeping all others the same.

[b] Time Period 40 assumes the observation period is 40 years.

[c] Variance 0.01 and 0.1 assume difference process variance values.

[d] Variance Degrees of Freedom columns assume different variance degrees of freedom values.

[e] Hatchery Fraction columns assume different fractions of hatchery-origin spawners in the population.
[f] QET 100 shows targets assuming a QET of a four-year average of 100 spawners per year.
[g] Extinction Risk columns assume an acceptable extinction risk of # percent in 100 years.
[h] Acceptable Time Horizon 200 assumes an acceptable extinction risk of 5% in 200 years.
[i] Marine Index Long-Term assumes the marine survival over the observation period was twice the long-term average.

Table D.4 Identical to Table D.3, except the targets are expressed as observed four-year average spawner abundances.

Current Size	Standard[a]	Time Period 40[b]	Variance[c]		Variance Degrees of Freedom[d]			Hatchery Fraction[e]			QET[f] 100	Extinction Risk[g]			Acceptable Time Horizon 200[h]	Marine Index Long-Term[i]
			.01	.1	5	10	40	5%	10%	30%		1	25	60		
100	600	1,200	200	1,400	1,100	700	500	1,060	>2,000	>2,000	800	1,000	300	200	700	700
150	800	1,400	300	1,800	1,500	900	700	1,459	2,797	>3,000	1,000	1,400	400	200	1,000	1,000
200	1,000	1,700	300	2,100	1,800	1,200	900	1,835	3,754	>4,000	1,200	1,700	500	200	1,200	1,200
500	1,900	3,000	700	4,300	3,200	2,200	1,900	3,613	7,618	>10,000	2,300	3,600	900	400	2,500	2,500
1,000	3,400	4,600	1,300	7,400	5,400	3,800	3,200	6,283	13,768	>20,000	3,900	6,500	1,500	700	4,600	4,400
1,500	4,700	6,000	1,900	9,600	7,400	5,400	4,500	8,938	19,358	>30,000	5,400	9,000	2,100	1,000	6,200	6,000
2,000	6,000	7,200	2,300	12,200	9,000	6,300	5,500	11,721	23,737	>40,000	6,800	12,000	2,600	1,200	8,000	7,100
2,500	7,100	8,500	2,800	14,700	11,100	8,200	6,800	14,191	28,397	>50,000	8,100	13,600	3,200	1,400	10,100	9,400
3,000	8,200	9,900	3,300	17,100	12,700	9,000	7,800	16,699	33,955	>60,000	9,400	15,600	3,600	1,700	11,700	10,300
3,500	9,700	10,900	3,800	19,200	14,800	11,000	9,000	18,349	39,406	>70,000	10,500	17,000	4,100	1,900	13,500	11,700
4,000	10,600	11,300	4,300	21,700	16,000	11,300	10,100	21,297	42,670	>80,000	11,300	20,200	4,600	2,100	14,900	13,800
4,500	11,400	12,500	4,600	24,000	17,500	12,800	10,800	23,032	47,254	>90,000	12,800	21,800	5,100	2,300	16,800	14,600
5,000	12,800	14,500	5,100	25,000	18,400	14,500	12,100	24,806	51,380	>100,000	14,600	23,400	5,500	2,500	18,800	15,900
6,000	14,800	15,900	6,000	30,300	22,800	16,100	14,100	29,057	61,153	>120,000	17,000	28,800	6,100	2,900	22,300	18,300
7,000	17,200	17,400	6,800	35,100	24,700	18,100	15,900	32,254	69,359	>140,000	18,800	32,100	7,300	3,300	25,500	21,900
8,000	17,500	18,700	7,700	36,900	27,900	20,600	18,300	37,051	80,045	>160,000	20,800	40,100	8,200	3,800	28,000	25,100
9,000	20,900	21,700	8,500	40,700	30,800	22,700	20,100	39,393	85,742	>180,000	23,400	39,600	8,900	4,100	32,100	25,900
10,000	21,700	23,600	9,200	45,100	34,400	24,700	21,900	45,669	93,802	>200,000	25,300	43,200	9,500	4,600	34,800	28,400

[a] This column describes the targets assuming standard conditions: for these analyses, they were a 20-year observation period, process variance of 0.05, 20 degrees of freedom for the variance estimate, 0 hatchery-origin spawners, a QET four-year average of 50 spawners per year, and an acceptable extinction risk of 5% in 100 years. The other target columns show target calculated by varying one of the standard assumptions and keeping all others the same.

[b] Time Period 40 assumes the observation period is 40 years.

[c] Variance 0.01 and 0.1 assume difference process variance values.

[d] Variance Degrees of Freedom columns assume different variance degrees of freedom values.

[e] Hatchery Fraction columns assume different fractions of hatchery-origin spawners in the population.

[f] QET 100 shows targets assuming a QET of a four-year average of 100 spawners per year.

[g] Extinction Risk columns assume an acceptable extinction risk of # percent in 100 years.
[h] Acceptable Time Horizon 200 assumes an acceptable extinction risk of 5% in 200 years.
[i] Marine Index Long-Term assumes the marine survival over the observation period was twice the long-term average.

Table D.5 Recent average abundance and fraction of hatchery origin for WLC populations.[a]

ESU	Population[b]	Year	Current Size	Hatchery Fraction
Columbia chum salmon	Grays River	1997–1998	874	0
	Lower gorge tributaries	1997–2000	542	0
	Upper gorge tributaries	1997–2000	100	
Upper Willamette steelhead	Mollala River	1997	574	24
	North Santiam River	1997	2,214	29
	South Santiam River	1997	900	0
	Calapooia River	1997	236	0
Upper Willamette chinook salmon	Clackamas River	1997–2000	1,453	
	McKenzie	1997–2000	1,904	24
Lower Columbia steelhead	North Fork Toutle River winter	1997–2000	176	0
	South Fork Toutle River winter	1997–2000	463	2
	Coweeman River winter	1998–2000	487	50
	Kalama River winter	1997–2000	554	0
	Clackamas River winter	1997–2000	465	39
	Sandy River winter	1997–2000	1,005	
	Hood River winter	1997–2000	850	52
	Kalama River summer	1997–2000	419	38
	East Fork Lewis summer	1997–2000	287	33
	Washougal River summer	1997–2000	158	8
	Wind River summer	1997–2000	368	10
	Hood River summer	1997–2000	866	82
Lower Columbia chinook salmon	Grays River fall	1997–2000	127	37
	Elochoman River fall	1997–2000	754	69
	Mill, etc. fall	1997–2000	491	47
	Lower Cowlitz fall	1997–2000	1,702	67
	Coweeman	1997–2000	425	0
	Kalama River fall	1997–2000	2,995	67
	Salmon Creek late fall	1997–2000	235	0
	Washougal River fall	1997–2000	3,231	57
	Sandy River fall	1997–2000	220	3
	Upper gorge tributaries fall	1997–2000	159	17
	Big White Salmon fall	1997–2000	234	21
	Sandy late	1997–2000	839	3
	North Fork Lewis bright	1997–2000	7,293	13
	Upper Cowlitz spring	1997–1999	365	
	Kalama River spring	1997–1999	105	0
	Lewis River spring	1997–1999	300	0

[a] The averages are standardized for the years 1997–2020: if data were missing over these years, the average was based on the existing data.
[b] This list does not include all WLC populations. Some populations are extirpated and have a current abundance of 0. For populations not in this table, there are no available abundance data.

Literature Cited

Anderson, J. J. 1998. Decadal climate cycles and declining Columbia River salmon. Sustainable Fisheries Conference Proceedings.

Barrowman, N., and R. Myers. 2000. Still more spawner-recruitment curves: The hockey stick and its generalizations. Can. J. Fish. Aquat. Sci. 57(4): 665–676.

Beamish, R. J., D. J. Noakes, G. A. MacFarlane, L. Klyshatorin, V. V. Ivanov, and V. Kurashov. 1999. The regime concept and natural trends in the production of Pacific salmon. Can. J. Fish. Aquat. Sci. 56: 516–526.

Dennis, B., P. L. Munholland, and J. M. Scott. 1991. Estimation of growth and extinction parameters for endangered species. Ecol. Monogr. 61: 115–143.

Dennis, B., and M. L. Taper. 1994. Density dependence in time series observations of natural populations: Estimation and testing. Ecol. Monogr. 64: 205–224.

Goodman, D. 1987. The demography of chance extinction. *In* M. E. Soulé (ed.), Viable populations for conservation. Cambridge University Press, Cambridge. p. 11–34.

Hare, S. R., N. J. Mantua, and R. C. Francis. 1999. Inverse production regimes: Alaska and west coast Pacific salmon. Fisheries 24: 6–14.

Hilborn, R., and C. J. Walters. 1992. Quantitative fisheries stock assessment: Choice, dynamics, and uncertainty. Chapman and Hall, New York.

Holmes, E. 2001. Estimating risks in declining populations with poor data. Proc. Nat. Acad. Sci. 98(9): 5072–5077.

Holmes, E. E., and W. F. Fagan. 2002. Validating population viability analysis for corrupted data sets. Ecology (in press).

Hooten, M. M. 1995. Distinguishing forms of statistical density dependence and independence in animal time series data using information criteria. M.S. Thesis. Montana State University, Bozeman, Mont.

Keller, L. F., and D. M. Waller. 2002. Inbreeding effects in wild populations. Trends in Ecol. Evol. 17(5): 230–232.

Lande, R. 1993. Risks of population extinction from demographic and environmental stochasticity and random catastrophes. Am. Natural. 142: 911–927.

Lande, R. 1998. Demographic stochasticity and Allee effect on a scale with isotropic noise. Oikos 83: 353–358.

Mantua, N. J., S. R. Hare, Y. Zhang, J. M. Wallace, and R. C. Francis. 1997. A Pacific interdecadal climate oscillation with impacts on salmon production. Bull. Amer. Meteorol. Soc. 78: 1069–1079.

McClure, M. M., E. E. Holmes, B. L. Sanderson, and C. E. Jordan. 2003 (in press). A large-scale, multi-species status assessment: Anadromous salmonids in the Columbia River Basin. Ecol. Apps.

McElhany, P., and J. Payne. In prep. Setting viability criteria for Pacific salmonids using abundance data.

McElhany, P., and J. Payne. In prep. Testing the robustness of an approach to viability criteria.

McElhany, P., M. H. Ruckelshaus, et al. 2000. Viable salmonid populations and the recovery of evolutionarily significant units. U.S. Dept. Commer., National Marine Fisheries Service, Northwest Fisheries Science Center, Seattle, Wash. 156.

Musick, J. A. 1999. Criteria to define extinction risks in marine fishes. Fisheries 24(12): 6–14.

Ray, C., and A. Hastings. 1996. Density dependence: Are we searching at the wrong spatial scale? J. Anim. Ecol. 65: 556–566.

Shenk, T. M., G. C. White, and K. P. Burnham. 1998. Sampling-variance effects on detecting density dependence from temporal trends in natural populations. Ecol. Monogr. 68: 445–463.

Sokal, R. R., and F. J. Rohlf. 1981. Biometry. W.H. Freeman and Company, New York.

Soulé, M. E. 1980. Thresholds for survival: Maintaining fitness and evolutionary potential. *In* M. E. Soulé and B. A. Wilcox, Conservation Biology. Sinauer Associates, Inc., Sunderland, Mass.

Thomas, C. D. 1990. What do real population dynamics tell us about minimum viable population sizes? Conserv. Biol. 4: 324–327.

Thomas, C. D., M. C. Singer, and D. A. Boughton. 1996. Catastrophic extinction of population sources in a butterfly metapopulation. Am. Natural. 148: 957–975.

Waples, R. S. 1990a. Conservation genetics of Pacific salmon. II. Effective population size and rate of loss of genetic variability. J. Hered. 81: 267–276.

Waples, R. S. 1990b. Conservation genetics of Pacific salmon. III. Estimating effective population size. J. Hered. 81: 277–289.

Wright, S. 1938. Size of population and breeding structure in relation to evolution. Science 87: 430–431.